PATTERN SEPARABILITY VISUAL FEEDBACK TO IMPROVE PATTERN RECOGNITION DECODING PERFORMANCE

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ABSTRACT

State-of-the-art myoelectric upper limb prostheses control often utilize pattern recognition (PR) systems that translate electromyograph (EMG) activity to a desired movement. As possible prosthesis movements increase, users have difficulty generating sufficiently separable EMG signals that reliably operate all possible degrees of freedom. Current training regimens attempt to increase the separability of a user's EMG signals through trial-and-error, where a therapist prompts a user to generate EMG signals and provides advice based on the strength and channel distribution of the EMG. In this work, we present a novel visual feedback interface that allows users to observe how their EMG signals affect PR output directly.

INTRODUCTION

Myoelectric control is a widely used method for the control of multi-articulated prosthetic devices. Myoelectric control operates by capturing electromyographic (EMG) signals generated during the user's muscle contractions and pattern recognition (PR) methods can be utilized to classify data into separate groups. Once these patterns of EMG activity have been established, they can serve as indicators for future EMG input, facilitating the identification of various movements [1]. While several factors contribute to the adoption of PR-based myoelectric control, low acceptance of prosthetic devices among individuals with upper limb loss (ULL) underscores significant challenges [2]. Experimental robustness does not necessarily equate to practical functionality and for novice users, there is often a steep learning curve to attain control proficiency [3]. Potential misclassifications can stem from a variety of environmental factors, including motion artifacts, electrode displacement, variations in limb positioning [4], and muscle fatigue. Furthermore, as the complexity and quantity of gestures employed in PR systems expand, the differentiation between each pattern becomes less discernible, leading to system confusion [5].

Previous literature has supported that human motor learning-based training plays a pivotal role in enhancing myoelectric PR-based prosthesis control, improving both accuracy and adaptability [6], [7], [8]. Existing training programs encompass various approaches, including motor imagery, which visually represents the picture of intended movements to the user, EMG training games that integrate proportional and derivative control into gameplay, and 2D virtual arm training that concurrently displays the user's movements on a screen [8], [9]. However, for a more defined separation of gesture classes, the core solution lies in either shifting the classes within the feature space to augment interclass distance or reducing intra-class variability [7]. Enhancing control strategy performance in the aforementioned training methods poses a challenge without insight into the underlying algorithm's performance, as users only have a 'black box' perspective of input-output interactions. This deficiency may obscure the understanding of a performance issue's origins, thereby limiting the users' ability to make informed, strategic adjustments, particularly as the complexity and number of gestures escalate [10].

In this work, we present a novel 3D visual feedback system designed to bridge the gap between the user and the pattern recognition system. Our system addresses the challenge of understanding the input-output control relationship in multi-gesture myoelectric control. PR training outcomes are showcased within a 3D interactive platform, wherein gesture relationships can be intuitively observed through their positioning in the feature space. Through this innovation, we aim to bolster the training-induced enhancement of control quality in myoelectric PR-based prostheses.

METHODS

This study was conducted in accordance with a protocol approved by the Johns Hopkins University School of Medicine Institutional Review Board. Twelve able-bodied participants, 6 males and 6 females, were recruited to take part in a 10-day longitudinal experiment. Participants varied in age from 18 to 22. No participants had previous experience with PR-based myoelectric control. Participant EMG signals were recorded using the 8 channel Myoband (Thalmic Labs, Ontario, Canada) positioned on the subject's dominant arm. Additionally, participants wore a bypass prosthesis to incorporate noise conditions from load and fatigue, and movements were performed in multiple spatial locations to incorporate the limb position effect.

Training Methods

Participants were provided one of two methods to visualize their control during the exploration period: (1) an experimental, 3D visualization of the pattern recognition decision-space; and (2) a controllable virtual arm (Figure 1).

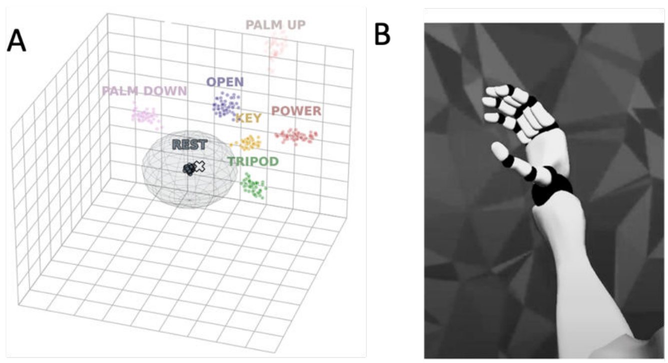

Figure 1. This figure shows the training methods employed in the study: (A) the 3D Visual System and; (B) the Virtual Arm.

The 3D control visualization projects the individual's incoming EMG data into the decision-space of the PR-based control method. This is accomplished by first undergoing a standard calibration regiment for PR-based control, where a calibration data set of EMG samples is collected on a class-by-class basis to generate a classifier. This calibration set is then projected into a 3-dimensional subspace, optimizing for low intra-cluster variability and high inter-cluster distance. During the evaluation periods, EMG activity of subjects was projected within the same training basis to represent where an individual's current EMG activity lies within the projection space. Within the visualization, the original training data is represented as coloured clusters of data points and the individual's current EMG activity is represented as a cursor. The cursor's position is modulated in real time by the user's EMG activity, allowing the participant to directly observe how their changing EMG patterns affect the proximity of their current pattern to the data the PR-based control method was calibrated with. In this way, participants receive direct visual feedback on the discriminability of their calibration data and the repeatability of their control as well as an opportunity to generate and observe how novel patterns of EMG activity map to regions of the decision-space (Figure 1a). In contrast, the virtual arm training method allows participants to operate a virtual model of an arm as if it were a real-world prosthesis (Figure 1b).

Experiment Protocols

Participants were evenly split into two groups of six, each comprising three males and three females: one experimental group utilizing the 3D visual feedback system, and a control group granted access to a real-time controllable virtual prosthesis. Each day, both participant groups underwent a calibration phase to capture EMG signals used for training the PR algorithm. From days 1 to 4, the participants performed a set of five gestures. This was increased to six distinct movements on day 5, and by day 7, they were executing a total of nine distinct movements (rest, open, power, pronation, supination, tripod, key, index point, pinch). Following the initial calibration phase, both participant groups were granted an exploration period to adjust their calibration data. Subjects had the flexibility to engage in practice sessions and refine their gestures if they found their control to be unsatisfactory and were allowed to recalibrate individual movements any number of times.

During this phase, the experimental group had access to real-time feedback from a 3D visual feedback system, while the control group had access solely to a virtual arm. To maintain consistency and fairness, time constraints were established for both groups: three minutes were allotted per movement (excluding rest). After the adaptation period, all participants' control proficiency was assessed following a Fitts Law assessment protocol (Figure 2c-d) [11].

During the testing phase, subjects were centrally positioned, with a display screen to their right and a numbered board to their left (Figure 2a). The screen presented the Fitts Law test and subjects were required to perform the task with alternating limb positions, with classified hand grasps modulating the size of the ring and classified wrist movements modulating its orientation. Each task had a time limit of 15 seconds. The total number of tasks was determined by the total number of gestures: four movements correspond to 18, six movements to 36, and eight movements to 54 tasks. The control proficiency of subjects was evaluated based on four metrics of the Fitts Law test: completion rate, overshoot per trial (OT), path efficiency (PE), and throughput (TP) [11].

An 11th session was completed 30 days after the last session to gauge the long-term impact of the 3D visual system with the exact same setup.

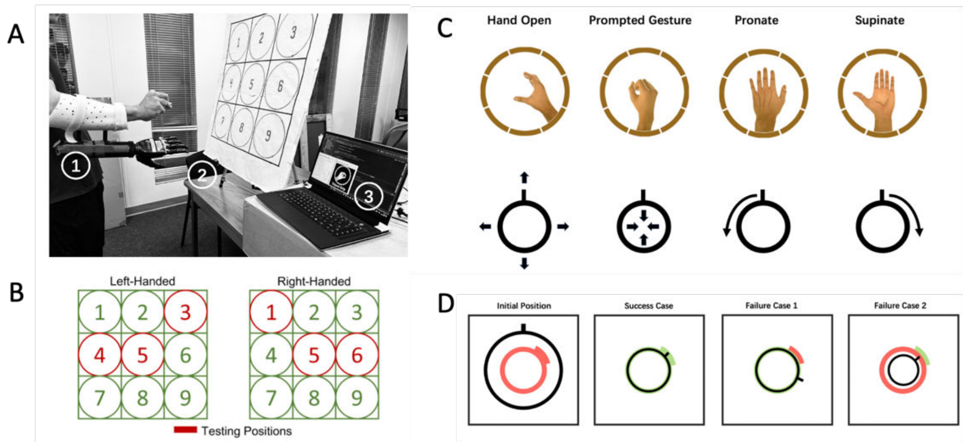

Figure 2. (A) Physical Setup for the Experiment: 1) a bypass prosthesis to emulate the weight-bearing experience; 2) a numbered board to achieve postural variance; and 3) a screen to display the Fitts Law Test. (B) An enumeration of the testing positions for the Fitts Law Tests. (C) In the Fitts Law Test, subjects will manoeuvre a black ring with open/close gestures, along with a protrusion on the ring with wrist rotation gestures. (D) Subjects are tasked with aligning to the red ring and protrusion. A trial is deemed successful only when both the ring and protrusion are aligned accurately within a timeframe of 15 seconds.

RESULTS

In this 10-day study involving twelve novice subjects, new movements were introduced in the first, fifth, and eighth sessions. As depicted in Figure 3a, the experimental group consistently outperformed the control group in terms of mean task completion rate.

A notable distinction between the two groups was observed in their ability to adapt to heightened control complexity. On the fifth day, the completion rate of the experimental group dipped from 0.97 ± 0.07 (mean ± standard deviation) to 0.83 ± 0.1 relative to the previous day, while the control group saw a more pronounced drop from 0.77 ± 0.23 to 0.51 ± 0.29. The divergence in performance was further amplified on the eighth day; the experimental group experienced a marginal decline in completion rate from 0.92 ± 0.12 to 0.86 ± 0.14 since day seven, whereas the control group exhibited a substantial decrement from 0.86 ± 0.07 to 0.46 ± 0.31. In both instances, the difference between the two groups was significant on the day following the introduction of new movements, a contrast to their previous day, where no significant difference was observed.

In terms of OT, PE and TP, the experimental group consistently outperformed the control group as shown on Figure 3b-d, although not at the rate indicated by the CR metric.

DISCUSSION

Throughout all sessions, the experimental group utilizing the 3D visual feedback system exhibited higher mean values for three metrics: CR, PE, and TP, and a lower mean for OT. This shows that the 3D system group surpassed the virtual arm group in all aspects of control proficiency. Based on feedback from participants, the experimental group reported less difficulty in modifying and fine-tuning movements and were able to refine their gestures effectively by observing overlaps in the visualization system. However, the results for OT, PE, and TP do not appear to align with the trend of increased control proficiency leading to increased differences between the two groups.

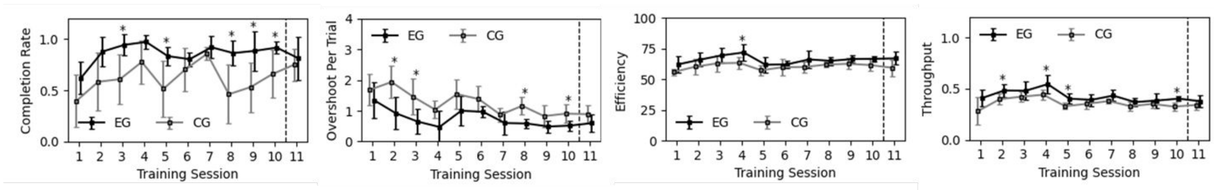

Figure 3. The results show the mean and standard deviation of the experimental group (EG) and control group (CG) over ten sessions, along with an additional return session conducted 30 days after session 10. In the span from session 1 to 4, four gestures were involved in calibration (excluding the resting position); in session 5, two additional movements were incorporated, and in session 8, two further movements were added. These movement differences separate the test into three segments. A dashed line delineates the return experiment results from the original test data. * indicate sessions wherein the difference between the experimental group and control group was statistically significant ($p < 0.05$).

The most plausible explanation for this affect is the decline in classification accuracy. Successfully executing the gestures required by the trial is crucial for task completion as well as incurring an overshoot, since overshoot is based on the over-application of the correct movement. This shows a limitation of this study, that a metric that captures failure to initialize an intended movement is missing.

The findings from the 11^{th} session continue to highlight the experimental group's superior performance in all mean values, however the gains washed out over the 30-day period, suggesting a diminishing advantage conferred by the 3D system on subjects when training is suspended.

ACKNOWLEDGMENTS

This work was supported by the National Institutes of Health NIH U44NS119842.

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